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Predicting Conversion from Pyrolysis of Pongamia

Nuttapol Lerkkasemsan*

Department of Chemical Engineering, Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang, Ladkrabang, 10520 Thailand

Abstract

This research demonstrates the technique of predicting pyrolysis of lignocellulosic biomass. Modeling of pyrolysis of biomass is complex and challenging because of short reaction times, temperatures as high as a thousand degrees Celsius, and biomass of varying or unknown chemical compositions. As such a deterministic model is not capable of representing the pyrolysis reaction system. To be able to predict a pyrolysis reaction of an unknown lignocellulosic biomass without an experimental data support or data fitting is an even more challenging work. In this research, we are trying to predict pyrolysis of Pongamia in Nitrogen to demonstrate that our technique is useful for predicting pyrolysis reaction of other biomass source. There are three main chemical compositions in lignocellulosic biomass which are cellulose, hemicellulose and lignin. We are considering that the total pyrolysis reaction is affected by the reaction of three main compositions. However, these three main chemical compositions of biomass is vary not only by type of biomass but also by other things such as where it is grown or even which part of biomass since the chemical compositions in the leaf can be different from the trunk. Our propose method is an extending study of our previous paper “pyrolysis of biomass – fuzzy modeling”. Our model successfully gives a good predicting result. The result shows that our model can predict 91.82% of pyrolysis of Pongamia in Nitrogen correctly without any data from the experiment. Therefore, we could use this method to predict other lignocellulosic biomass before we perform an experiment.

Keywords: Renewable Energy; Pyrolysis Modeling; Fuzzy Logic; ANFIS

1. Introduction

There are many ways to convert biomass to an easy-to-use form. The thermochemical conversion of biomass processes (namely pyrolysis, gasification, and combustion) is a promising process for future energy supply. The process is easy to scale up to industry size. Pyrolysis is the thermal degradation of biomass in the absence of oxygen. The three main products from pyrolysis of biomass are charcoal, bio-oil and gaseous product; these are more useful energy holders. Bio-oil and gaseous product are chemical resources for the refinery plant. In order to develop an efficient pyrolysis process, a determination of key pyrolysis parameters and their effect on the process is essential. In many studies, pyrolysis kinetic models are relatively simple but useful. The models in those cases only predict the overall yield of pyrolysis process without considering the physicochemical mechanism of the process.

Although there are many studies on biomass pyrolysis, there is a severe lack of models for predicting the pyrolysis rate and final conversion under a wide range of process conditions and biomass

feedstock compositions. Modeling the biomass pyrolysis is complicated by many factors. Biomass is a complex mixture of several organic compounds and polymers. Thus it is a challenge to identify all the molecular species as well as quantify the composition of the known molecular species. Moreover, there are hundreds of reactions that take place during pyrolysis reactions. Most of the existing models are specific to a particular biomass source – this limits the range of applicability of the model. Li(1) studied the pyrolysis of corn straw. For example Chiang(2) considered the kinetics of rice hulk pyrolysis. Gašparović(3) proposed a distribution activation energy model (DAEM) to describe the pyrolysis decomposition of wood. The model is able to describe an integral decomposition curve for wood but fails to describe the differential curve. In general, DAEM does not accurately describe biomass pyrolysis.

We propose the use of ANFIS to model biomass pyrolysis considering the modeling challenges discussed earlier. We employ ANFIS to relate affect of three main chemical compositions which are cellulose, hemicellulose and lignin to the total pyrolysis reaction of Pongomia in Nitrogen.

2. Methodology

The ANFIS system employs fuzzy modeling first introduced by Lotfi Zadeh(4). Problems such as human reasoning in an imprecise environment can be handled using fuzzy logic theory. The theory is particularly applicable to uncertain problems, such as what occurs in pyrolysis. The ANFIS combines fuzzy logic concepts (Takagi-Sugeno fuzzy inference) with neural network concepts. (5)(6). While Artificial Neural network (ANN) has the ability to learn from a system, the ANN knowledge is stored in an unreadable table, which is hard to interpret. On the other hand, the fuzzy inference system is able to translate the unreadable table into human language. However, the fuzzy system by itself lacks a learning ability and thus the membership function parameters have to be manually tuned. The combination of ANN and fuzzy inference system creates an approximator that has the ability to learn from samples and translate the unreadable result into human language.

In ANFIS, the set of parameter values is systematically modified using the training data and a learning algorithm. The basic learning method is gradient based; this is slow and tends to be trapped in a local minimum. In contrast the ANFIS model uses a faster hybrid learning algorithm. The hybrid learning algorithm combines least-squares estimator and the gradient descent method. There are two passes in the hybrid algorithm; the forward pass calculates the vectors, which are outputs from each node in each layer. The backward pass uses a steepest descent algorithm (5)(6).

The parameter set S can be divided into two sets as

$$S = S_1 \oplus S_2 \quad (1)$$

where \oplus represent direct sum.

S = set of total parameters

S_1 = set of premise parameters which is nonlinear parameters

S_2 = set of consequent parameters which is linear parameters

In the forward pass, the parameter S_2 is calculated and modified using the least square estimator method, while S_1 is unmodified.

In the backward pass, the parameter S_1 is calculated and modified using the steepest descent, while S_2 is not modified.

Through this hybrid learning method, the parameters in ANFIS are updated.

3. Result and discussion

Since there are a lot of uncertainties in the pyrolysis, the deterministic model which is designed to model a well-defined system fails to model the pyrolysis as we showed in previous paper (7). Here, we tackle the same problem while considering uncertainty. ANFIS is utilized to model the pyrolysis reaction. We have developed the model based on an individual effect of three main chemical components inside the biomass on the pyrolysis reaction. In this research, we have developed the model to predict the pyrolysis conversion of Pongomia in Nitrogen. The result of the model is shown below.

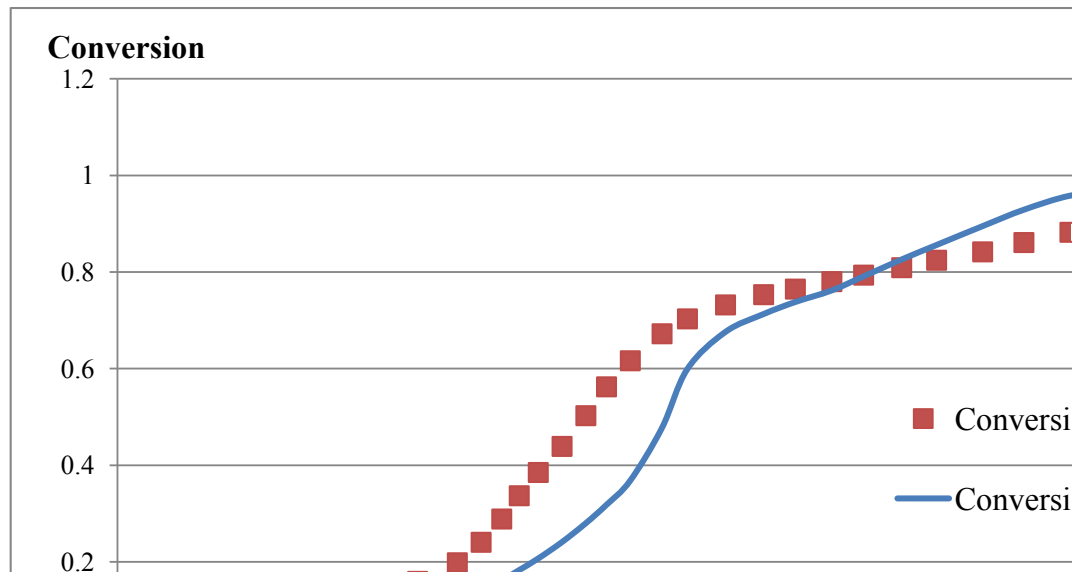


Figure 1 Prediction of pyrolysis of pongmia from model vs conversion from experiment

Figure 1 displays the result from our ANFIS model vs experimental data. The data took from the work of Gottipati & Mishra (8). The experimental data is performed at heating rate of 10°C/min in Nitrogen. The results from the ANFIS model are similar curve to the experimental data. The coefficient of determination from model and experimental data is 0.92. It demonstrates that the model can predict the pyrolysis of Pongomia in Nitrogen.

After we successfully delivered a good prediction for pyrolysis of Pongomia in Nitrogen, we can try to deliver prediction of pyrolysis of other lignocellulosic biomass. With a good prediction model, we can open a new aspect of modeling of pyrolysis of biomass. Instead of doing a model fitting with experimental data, we can predict pyrolysis of other lignocellulosic biomass source before we perform experiment. It is going to be a useful source of information for experimentalist before they perform their experiment.

4. Summary

We were inspired to use this model due to the uncertainty in the pyrolysis of biomass. Modeling is complex because of short reaction times, temperatures as high as a thousand degree Celsius, and biomass of unknown chemical compositions. Deterministic models, such as the first order reaction model, may not be able to give a good prediction of the reaction. The results from the ANFIS model give a good prediction when testing the model with the experimental data. The result shows that our model can predict 91.82% of pyrolysis of Pongmia in Nitrogen correctly without any data from the experiment. Therefore, we could use this method to predict other lignocellulosic biomass before we perform an experiment.

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